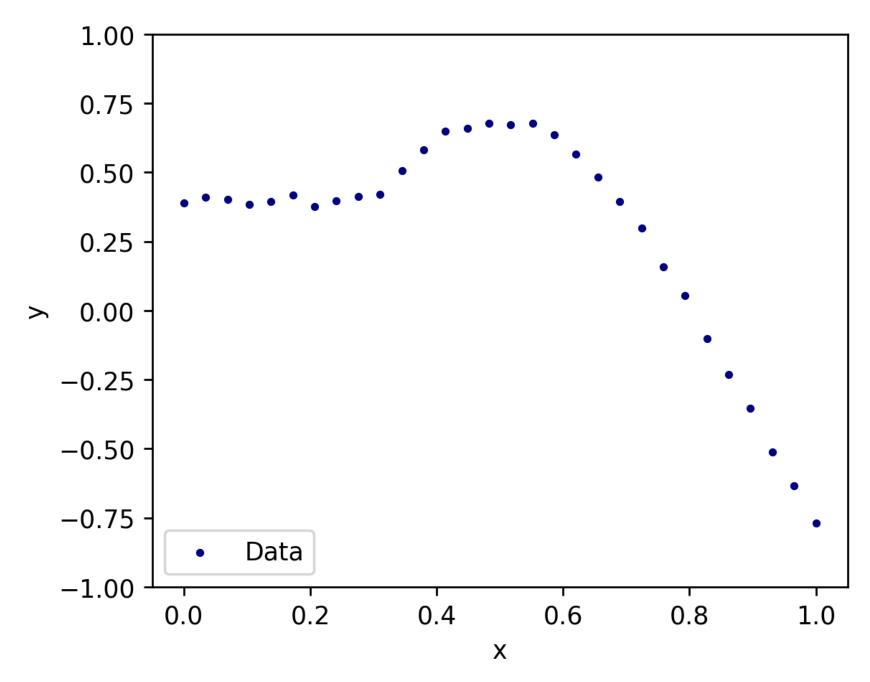
M7-L2 Problem 2

Here you will create a simple neural network for regression in PyTorch. PyTorch will give you a lot more control and flexibility for neural networks than SciKit-Learn, but there are some extra steps to learn.

Run the following cell to load our 1-D dataset:

```
import numpy as np
In [34]:
                                             import matplotlib.pyplot as plt
                                             import torch
                                             from torch import optim, nn
                                             import torch.nn.functional as F
                                             x = np.array([0.
                                                                                                                                                           , 0.03448276, 0.06896552, 0.10344828, 0.13793103, 0.17241379, 0.20689655, 0.24137931, 0.27586207
                                             y = np.array([0.38914369, 0.40997345, 0.40282978, 0.38493705, 0.394214, 0.41651437, 0.37573321, 0.39571087, 0.40282978, 0.38493705, 0.394214, 0.41651437, 0.37573321, 0.39571087, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.40282978, 0.4028
                                             plt.figure(figsize=(5,4),dpi=250)
                                             plt.scatter(x,y,s=5,c="navy",label="Data")
                                             plt.legend(loc="lower left")
                                            plt.ylim(-1,1)
                                             plt.xlabel("x")
                                             plt.ylabel("y")
                                             plt.show()
```



PyTorch Tensors

PyTorch models only work with PyTorch Tensors, so we need to convert our dataset into a tensors.

To convert these back to numpy arrays we can use:

```
x.detach().numpy()y.detach().numpy()
```

```
In [35]: x = torch.Tensor(x)
y = torch.Tensor(y)
```

PyTorch Module

We create a subclass whose superclass is nn.Module, a basic predictive model, and we must define 2 methods.

nn.Module subclass:

- __init__()
 - runs when creating a new model instance
 - includes the line super().__init__() to inherit parent methods from nn.Module
 - sets up all necessary model components/parameters
- forward()
 - runs when calling a model instance
 - performs a forward pass through the network given an input tensor.

This class Net_2_layer is an MLP for regression with 2 layers. At initialization, the user inputs the number of hidden neurons per layer, the number of inputs and outputs, and the activation function.

```
class Net_2_layer(nn.Module):
    def __init__(self, N_hidden=6, N_in=1, N_out=1, activation = F.relu):
        super().__init__()
        # Linear transformations -- these have weights and biases as trainable parameters,
        # so we must create them here.
        self.lin1 = nn.Linear(N_in, N_hidden)
        self.lin2 = nn.Linear(N_hidden, N_hidden)
        self.lin3 = nn.Linear(N_hidden, N_out)
        self.act = activation
```

```
def forward(self,x):
    x = self.lin1(x)
    x = self.act(x)  # Activation of first hidden layer
    x = self.lin2(x)
    x = self.act(x)  # Activation at second hidden layer
    x = self.lin3(x)  # (No activation at last layer)
    return x
```

Instantiate a model

This model has 6 neurons at each hidden layer, and it uses ReLU activation.

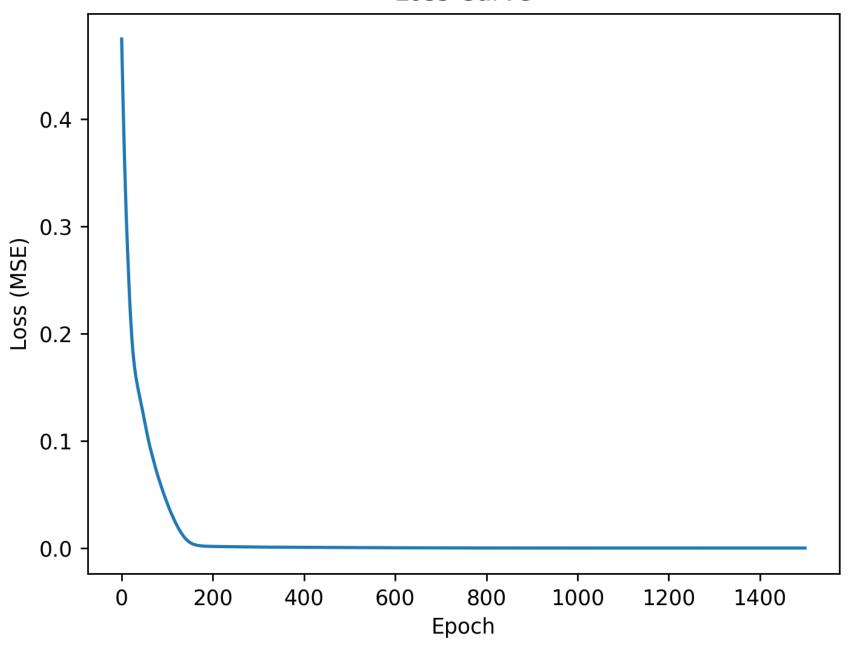
```
In [37]: model = Net_2_layer(N_hidden = 6, activation = F.relu)
loss_curve = []
```

Training a model

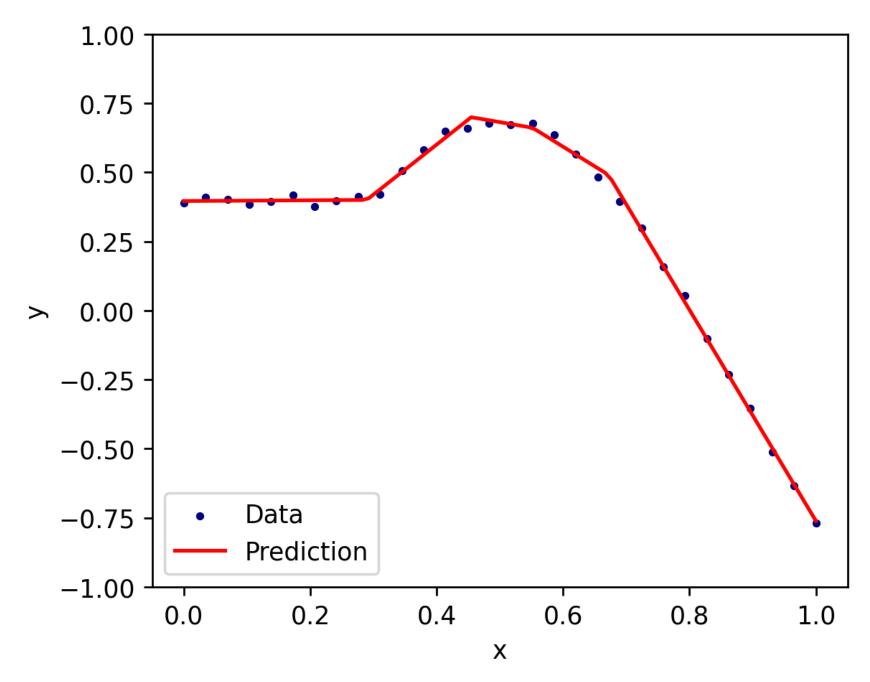
```
In [38]: # Training parameters: Learning rate, number of epochs, loss function
         # (These can be tuned)
         1r = 0.005
         epochs = 1500
         loss_fcn = F.mse_loss
         # Set up optimizer to optimize the model's parameters using Adam with the selected learning rate
         opt = optim.Adam(params = model.parameters(), lr=lr)
         # Training Loop
         for epoch in range(epochs):
             out = model(x) # Evaluate the model
             loss = loss_fcn(out,y) # Calculate the loss -- error between network prediction and y
             loss curve.append(loss.item())
             # Print loss progress info 25 times during training
             if epoch % int(epochs / 25) == 0:
                  print(f"Epoch {epoch} of {epochs}... \tAverage loss: {loss.item()}")
             # Move the model parameters 1 step closer to their optima:
             opt.zero_grad()
```

```
loss.backward()
             opt.step()
         Epoch 0 of 1500...
                                  Average loss: 0.4744042158126831
         Epoch 60 of 1500...
                                  Average loss: 0.09833034127950668
         Epoch 120 of 1500...
                                  Average loss: 0.022363871335983276
         Epoch 180 of 1500...
                                  Average loss: 0.002071716357022524
         Epoch 240 of 1500...
                                  Average loss: 0.0014897839864715934
         Epoch 300 of 1500...
                                  Average loss: 0.0011637693969532847
                                 Average loss: 0.001006523729301989
         Epoch 360 of 1500...
         Epoch 420 of 1500...
                                  Average loss: 0.0008361965301446617
         Epoch 480 of 1500...
                                  Average loss: 0.0006972100818529725
         Epoch 540 of 1500...
                                  Average loss: 0.0005636118003167212
         Epoch 600 of 1500...
                                 Average loss: 0.0004662715655285865
         Epoch 660 of 1500...
                                  Average loss: 0.00039241608465090394
         Epoch 720 of 1500...
                                 Average loss: 0.00032601619022898376
         Epoch 780 of 1500...
                                 Average loss: 0.0002884758869186044
         Epoch 840 of 1500...
                                 Average loss: 0.00026762307970784605
         Epoch 900 of 1500...
                                  Average loss: 0.0002573389501776546
         Epoch 960 of 1500...
                                  Average loss: 0.00025288251345045865
         Epoch 1020 of 1500...
                                  Average loss: 0.000250950368354097
                                  Average loss: 0.00025012611877173185
         Epoch 1080 of 1500...
                                  Average loss: 0.00024947928613983095
         Epoch 1140 of 1500...
         Epoch 1200 of 1500...
                                  Average loss: 0.00024902066797949374
         Epoch 1260 of 1500...
                                  Average loss: 0.00024853990180417895
         Epoch 1320 of 1500...
                                  Average loss: 0.00024804612621665
         Epoch 1380 of 1500...
                                  Average loss: 0.00024762339307926595
         Epoch 1440 of 1500...
                                 Average loss: 0.0002470871841069311
         plt.figure(dpi=250)
In [39]:
         plt.plot(loss_curve)
         plt.xlabel('Epoch')
         plt.ylabel('Loss (MSE)')
         plt.title('Loss Curve')
         plt.show()
```

Loss Curve



```
plt.figure(figsize=(5,4),dpi=250)
plt.scatter(x,y,s=5,c="navy",label="Data")
plt.plot(xs.detach().numpy(), ys.detach().numpy(),"r-",label="Prediction")
plt.legend(loc="lower left")
plt.ylim(-1,1)
plt.xlabel("x")
plt.ylabel("y")
plt.show()
```



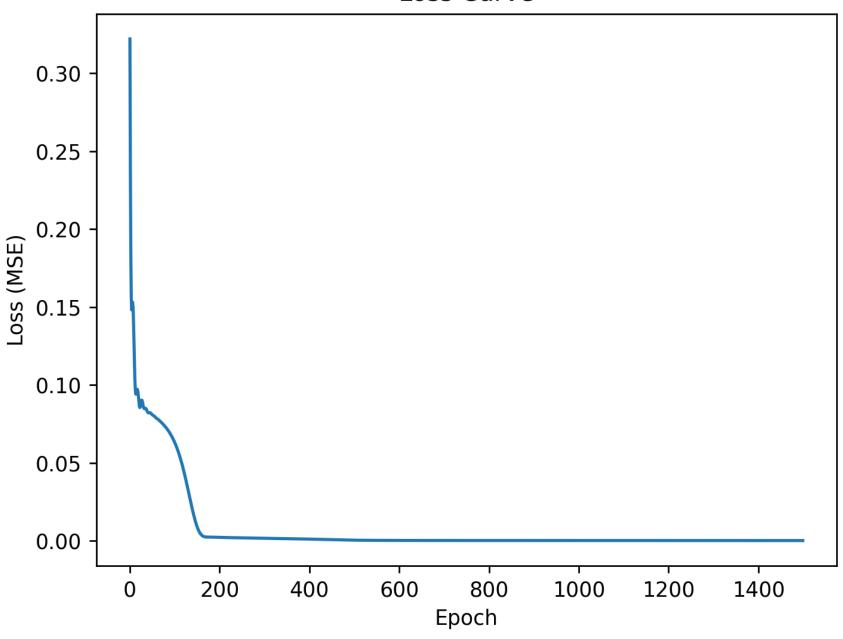
Your Turn

In the cells below, create a new instance of Net_2_layer . This time, use 20 neurons per hidden layer, and an activation of F.tanh . Plot the loss curve and a visualization of the prediction with the data.

```
In [41]: # YOUR CODE GOES HERE
          model = Net_2_layer(N_hidden = 20, activation = F.tanh)
          loss_curve = []
In [42]: 1r = 0.005
          epochs = 1500
          loss_fcn = F.mse_loss
          opt = optim.Adam(params = model.parameters(), lr=lr)
          # Training Loop
          for epoch in range(epochs):
             out = model(x)
             loss = loss_fcn(out,y)
             loss_curve.append(loss.item())
             if epoch % int(epochs / 25) == 0:
                  print(f"Epoch {epoch} of {epochs}... \tAverage loss: {loss.item()}")
             opt.zero_grad()
             loss.backward()
             opt.step()
```

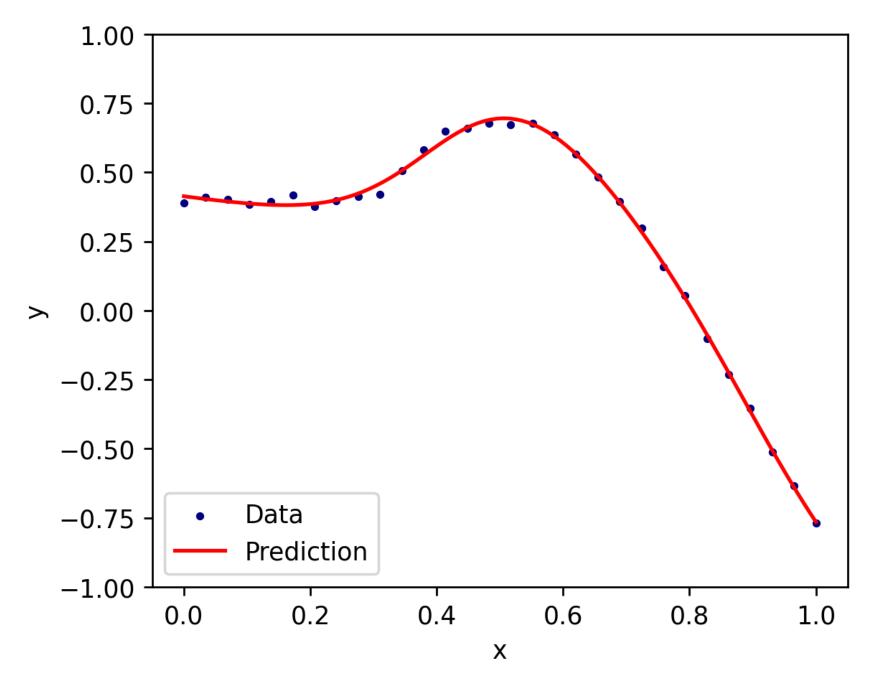
```
Epoch 0 of 1500...
                                  Average loss: 0.3219418227672577
         Epoch 60 of 1500...
                                  Average loss: 0.07849700003862381
         Epoch 120 of 1500...
                                  Average loss: 0.044798869639635086
         Epoch 180 of 1500...
                                  Average loss: 0.0024474714882671833
         Epoch 240 of 1500...
                                  Average loss: 0.002022543689236045
         Epoch 300 of 1500...
                                  Average loss: 0.0017344001680612564
         Epoch 360 of 1500...
                                  Average loss: 0.0014220451703295112
         Epoch 420 of 1500...
                                  Average loss: 0.0010031410492956638
         Epoch 480 of 1500...
                                  Average loss: 0.0005750214913859963
         Epoch 540 of 1500...
                                  Average loss: 0.0003725489950738847
                                  Average loss: 0.00030775790219195187
         Epoch 600 of 1500...
         Epoch 660 of 1500...
                                  Average loss: 0.0002830736921168864
         Epoch 720 of 1500...
                                  Average loss: 0.00027152951224707067
         Epoch 780 of 1500...
                                  Average loss: 0.00026513481861911714
         Epoch 840 of 1500...
                                  Average loss: 0.00026069581508636475
         Epoch 900 of 1500...
                                  Average loss: 0.0002569577773101628
         Epoch 960 of 1500...
                                  Average loss: 0.0002534904342610389
         Epoch 1020 of 1500...
                                  Average loss: 0.0002501792914699763
                                  Average loss: 0.000247005868004635
         Epoch 1080 of 1500...
         Epoch 1140 of 1500...
                                  Average loss: 0.00024397413653787225
                                  Average loss: 0.00024108236539177597
         Epoch 1200 of 1500...
         Epoch 1260 of 1500...
                                  Average loss: 0.00023832437000237405
         Epoch 1320 of 1500...
                                  Average loss: 0.00023568874166812748
         Epoch 1380 of 1500...
                                  Average loss: 0.00023316477017942816
         Epoch 1440 of 1500...
                                  Average loss: 0.0002307366085005924
In [43]:
         plt.figure(dpi=250)
          plt.plot(loss curve)
         plt.xlabel('Epoch')
          plt.ylabel('Loss (MSE)')
          plt.title('Loss Curve')
          plt.show()
```





```
In [44]: xs = torch.linspace(0,1,100).reshape(-1,1)
ys = model(xs)
```

```
plt.figure(figsize=(5,4),dpi=250)
plt.scatter(x,y,s=5,c="navy",label="Data")
plt.plot(xs.detach().numpy(), ys.detach().numpy(),"r-",label="Prediction")
plt.legend(loc="lower left")
plt.ylim(-1,1)
plt.xlabel("x")
plt.ylabel("y")
plt.show()
```



In []: